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Algorithm for the computation of region-based image edge profile acutance

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Abstract. *We propose an algorithm for the computation of a region-based measure of image edge profile (IEP) acutance based on gray-level variations across the boundary of an object. A procedure to calculate the acutance based on region growing and a root-mean-squared gradient measure across region boundaries has been designed and implemented. After testing the algorithm on various images, it is shown that this measure of acutance can accurately reflect changes in the appearance of objects due to blurring and sharpening operations. Using this technique, it should be possible to quantify the level of enhancement in a digital image by calculating the acutance before and after the enhancement operation. The measure should also be useful in comparing specific features or regions of interest in images produced by different imaging systems.*

1 Introduction

Images have been recorded and rendered on various media in the course of developments in imaging science and technology. Currently used media include photographic film, medical x-ray film, television monitors with varying number of lines per frame and frame repetition rate, and digital image archival media. The processes of capturing natural scenes or objects as images on any imaging or image representation system involves some limitations, anomalies, and loss of quality. This has led to many attempts to quantify image quality, which is an inherently subjective concept dependent upon not only various characteristics of the image in question, but also viewing conditions and the visual system of the viewer.[1-14] The field of digital image processing includes numerous techniques for improving various aspects of image quality, such as sharpness, contrast, dynamic range, and distributions of gray levels and frequency content.[15-19] However, judging the degree of improvement in quality provided by an image processing operation is a rather difficult task. Further, in the field of medical imaging, given an array of imaging systems for a certain mode of imaging, it is difficult to compare images produced by one system against those of another. It is even more difficult to objectively assess the quality of images produced by a system, as for example in imaging a certain feature such as a tumor.

The need for objective correlates of the subjective property of image sharpness or crispness has been recognized for a long time,[7] and various measures have been proposed by many researchers. Perrin,[5] Schade,[6] Task et al.,[2] Higgins,[1] Burke and Snyder,[4] and Barten[3] have published major review papers discussing many different measures of image quality and methods of appraising photographic and other imaging systems. Some commonly encountered measures of image quality include resolving power in terms of resolution charts, gratings, and test patterns; point, line, and edge spread functions (PSF, LSF, and ESF, respectively); contrast transfer functions; and the modulation transfer function (MTF) in the frequency domain.[15-17,20,21] However, it has been recognized by various researchers that measures based on resolution power are misleading and illusory, while spread functions and MTFs are not easy to compare, comprehend, or tabulate.[7]

In the search for a single measure that could represent the combined effects of various imaging and display processes, many researchers have proposed various measures under the general label of "acutance."[5,7,8,12-14,22] These measures combine the areas under the MTF curves of the long chain of systems and processes involved from the initial stage of the camera lens, through the film and/or display device, to

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the final visual system of the human viewer.[14] By design, they represent the combined effect of all the systems between the image source and the viewer; however, they are independent of the actual image displayed. We have been interested in developing a measure of sharpness or acutance of specific features or regions of a given image, in order to evaluate the effects of various image processing operations on specific image features.[23] The following section presents a historical review of various papers published on different aspects of image quality, with special attention to measures of acutance and sharpness and leading toward the measure proposed in this paper.

2 A Historical Review of Measures of Image Acutance and Sharpness

In 1952, Higgins and Jones[8] discussed the nature and evaluation of the sharpness of photographic images, with particular attention to the importance of gradients. Noting that cones in photopic vision respond to temporal illuminance gradients, and that the eye moves to scan the field of vision, they argued that spatial luminance gradients in the visual field represent physical aspects of the object or scene that control perception of detail. They conducted experiments with microdensitometer traces of knife edges on various photographic materials, and found that the maximum gradient or average gradient measures along the knife-edge spread functions (KESF) failed to correlate with sharpness. They then computed the mean-squared gradient across the KESFs, named it "acutance," and evaluated 10 different photographic materials with this measure. Their results indicated excellent correlation between "acutance" and subjective judgment of sharpness. The only inconclusive part of the study was the question of normalization with respect to the density difference across the knife edge.

Wolfe and Eisen[10] reported in 1953 on psychometric evaluation of sharpness of photographic reproductions. They stated that resolving power, maximum gradient, and average gradient do not correlate well with sharpness, and that variations of density across an edge is an obvious physical measurement to be investigated to obtain an objective correlate of sharpness. Perrin[5] continued along these lines, and (in 1960) proposed an averaged measure of "acutance" by averaging the mean-squared gradient measure of Higgins and Jones over many sections of the KESF and normalizing with respect to the density difference across the knife edge. He also discussed the relationship between the edge trace and the LSF.

In 1955 and 1956 Schade published two major papers dealing with image gradation, graininess, and sharpness in television and motion-picture systems[9] and on an optical and photoelectric analog of the eye.[24] He followed these with another major paper in 1964 on evaluation of photographic image quality and resolving power.[6] In these papers he discussed in detail the sine-wave, edge-transition, and square-wave responses of imaging systems. He gave detailed analysis of the relationships between resolving power, contrast sensitivity, number of perceptible gray-scale steps, and granularity with what he called the "three basic characteristics" of an imaging system: intensity transfer function, sine-wave response (spatial frequency spectrum), and signal-to-noise ratio (SNR). He also presented experimental setups and procedures with optical benches and equipment for photoelectric measurements and characterization of optical and imaging systems.

Although Perrin[5] reported on an averaged "acutance" measure based on the mean-squared gradient measure of Higgins and Jones, in Part II of the same paper[11] he remarked that the sine-wave response better describes the behavior of an optical system than a single parameter (such as resolving power), and discussed the relationship between the sine-wave response and spread functions. The works of Schade and Perrin perhaps shifted interest from the spatial gradient technique of Higgins and Jones to the frequency domain: A paper in 1964 by Crane[7] started a series of definitions of acutance based on frequency domain MTFs of imaging system components. (We shall now drop the quotes around the word acutance, as this word is now taken for granted to mean an MTF-based measure.) Crane[7] discussed the need for objective correlates of the subjective property of image sharpness or crispness, and remarked that resolving power is misleading, that the averaged squared gradient of edge profiles is dependable but cannot include the effects of all components in a photographic system (camera to viewer), and that spread functions and MTFs are not easy to comprehend, compare, or tabulate. He proposed a single numerical rating based on the areas under the MTF curves of all the systems in the chain from the camera to the viewer (camera, negative, printer, intermediate, ..., print film, projector, screen, and observer). He called this measure "system modulation transfer or SMT acutance" (SMTA) and claimed that it could be readily comprehended, compared, and tabulated. He also proposed that the acutance measure proposed by Higgins and Jones[8] and Perrin[5] be called "image-edge profile or IEP acutance" (IEPA) (which is the name we have used for the measure proposed in this paper as well). Crane evaluated 30 color films and motion-picture films using SMTA and found it to be a good tool.

Crane's work started another series of papers with various authors using modified definitions of MTF-based acutance measures for various applications: In 1973, Gendron[14] proposed a "cascaded modulation transfer or CMT" measure of acutance (CMTA) to rectify some deficiencies in SMTA. Crane himself wrote another paper in 1981 on acutance and granulance[22] and defined "AMT acutance" (AMTA) based on the ratio of the MTF area of the complete imaging system including the human eye to that of the eye alone. He also presented measures of granulance based on root-mean-squared (rms) deviation from mean lightness in areas meant to be uniform, and discussed the relationships between acutance and granulance. CMTA was used by Kriss[13] (in 1990) to compare system sharpness of continuous and discrete imaging systems and AMTA was used by Yip[12] in 1992 to analyze imaging characteristics of cathode ray tube (CRT) multiformat printers.

A number of authors have presented and discussed various other image quality criteria and measures that are worth mentioning here; while some are based on the MTF and hence have some common ground with acutance, others are based on different factors. In 1971, Higgins discussed various methods for analyzing photographic systems, including the effects of nonlinearity, line spread functions, MTFs, granularity, and sharpness.[25] In 1972, Granger and Cupery[26] proposed a "subjective quality factor (SQF)" based upon the integral of the

system MTF (including scaling effects to the retina) over a certain frequency range. Their results indicated a correlation between SQF and subjective ranking by observers of 0.988. Higgins[1] also presented a detailed review of various image quality criteria in 1977. He discussed quality criteria as related to objective or subjective tone reproduction, sharpness, and graininess. He reported on the results of tests evaluating various versions of MTF-based acutance and other measures with photographic materials having widely different MTFs, and recommended that MTF-based acutance measures are good when no graininess is present; SNR-based measures were found to be better when graininess was apparent. Task et al.[2] published a report on comparison of several television (TV) display image quality measures in 1978. Their tests included target recognition tasks and several figures of merit (FOM), such as limiting resolution, MTF area (MTFA), threshold resolution, and gray-shade frequency product (GFP). They found MTFA to be the best measure of the set evaluated.

In 1980 Carlson and Cohen[27] presented a psychophysical model for predicting the visibility of displayed information, combining the effects of MTF, noise, sampling, scene content, mean luminance, and display size. They noted that edge transitions are a significant feature of most scenes, and proposed "discriminable difference diagrams (DDDs)" of modulation transfer versus retinal frequency (in cycles per degree). Their work indicated that DDDs could be used to predict the visibility of MTF changes in magnitude but not in phase.

Burke and Snyder[4] reported in 1981 on quality metrics of digital images as related to interpreter performance. Their test set included a large collection of 250 transparencies of 10 digital images, each degraded by five levels of blurring and five levels of noise. Their work addressed the question "how can we measure the degree to which images are improved by digital processing." Results obtained indicated that though the main effect of blur was not significant in the interpretation experiment (in terms of extraction of "essential elements of information" or EEIs), that of noise was significant.

In spite of all of the preceding works, Hall[28] stated in 1981 that "A major problem which has plagued image processing has been the lack of an effective image quality measure." In his paper on subjective evaluation of a perceptual quality metric, Hall discussed standard image quality measures including mean squared error (MSE), normalized MSE (NMSE), normalized error, and Laplacian MSE (LMSE), and then defined a "perceptual MSE" or PMSE based on a human visual system model. (All of these measures are presumably based upon differences between a given degraded image and its "original" version, computed over the full image frame either directly or after some filter or transform operation.) His results showed that PMSE correlated well with subjective ranking of images to greater than 99.9% and performed better than NMSE or LMSE.

Westerink and Roufs[29] published a report in 1988 on a local basis for perceptually relevant resolution measures. Their experiments included presentation of a number of slides with complex scenes at variable resolution as created by defocusing the lens of the projector and at various widths. They showed that the width of the LSF correlates well with subjective quality, and remarked that MTF-based measures "do not reflect the fact that local aspects such as edges and contours play an important role in the quality sensation."

More recently, Barten[3] presented a review of various image quality measures in his paper on the evaluation of subjective image quality with the square-root integral (SQRI) method. The SQRI is based upon the ratio of the MTF of the display system to that of the eye, and can take into account contrast sensitivity of the eye and various display parameters such as resolution, addressability, contrast, luminance, display size, and viewing distance. The SQRI measure overcomes some limitations in the SQF measure of Granger and Cupery.[26] Based on good correlation between the SQRI and perceived subjective image quality, Barten proposed SQRI as an "excellent universal measure of perceived image quality."

As an aside, it is important to note the distinction between acutance and acuity. Westheimer published two papers in 1977 and 1979 where he discussed the concepts of visual acuity and hyperacuity[30,31] and their light-spread and spatial frequency descriptions. Acuity (as tested with Snellen letters or Landolt Cs) tests the "minimum separable," where the visual angle of a small feature is varied until a discrimination just can or cannot be made (a resolution task). On the other hand, hyperacuity (vernier or stereoscopic acuity) relates to spatial localization or discrimination.

Our interest has been in developing a local measure of quality, sharpness, or perceptibility of a region or feature of interest in a digital image. The question asked is "given two images of the same scene, which one permits better perception of a specific region or object in the image." Such a situation may arise in, for example, medical imaging, where one may have an array of images of the same patient or phantom test object acquired using different imaging systems (different models, different manufacturers, or different exposure settings on the same system). It would be of interest to determine which system or set of parameters would provide an image where a specific object, such as a tumor, may be seen best. While local luminance gradients are indeed reflected as changes at all frequencies in the MTF, such a global characteristic may dilute the desired difference in the situation mentioned above. Further, all MTF-based measures of acutance characterize imaging and viewing systems in general, and are completely independent of the specific object or scene presented. The fact that these measures are independent of the image under consideration is just cause to consider local measures of feature sharpness. Given the observations of Higgins and Jones,[8] Wolfe and Eisen,[10] Perrin,[5] Carlson and Cohen,[27] and Westerink and Roufs[29] on the importance of local luminance variations, gradients, contours, and edges (as reviewed earlier), we developed an interest in deriving a region-based measure of sharpness or "acutance" (as defined first by Higgins and Jones[8]). Acutance as measured by Higgins and Jones[8] and Perrin[5] was limited to images of knife edges. We propose in this paper a measure of mean-squared gradient computed across and around the contour of an object or region in a digital image. Given the background of acutance measures proposed in the past, we propose to call the quantity "a region-based measure of image edge profile or IEP acutance (IEPA)." The following sections provide details of computation of the measure and results obtained from a few experiments with digitally processed images. This paper is limited to details of computation of the measure and evalu-

ation with a few digital images; psychovisual experiments on correlation of the proposed measure with subjective perception of quality or sharpness with large numbers of images and observers has been left for the future.

3 A Region-Based Algorithm for Image Edge Profile Acutance

The first step in our algorithm for acutance is to get information on the boundary of the region of interest. The boundary of a region may be determined by using one of the many edge detection methods available.[15] In this work we use a region-growing method for edge detection.[32] This method starts with a seed pixel within the region of interest, and compares every 4-connected pixel with the seed. Connected pixels within a specified gray-level tolerance with respect to the seed pixel value are included in the region, and the process is continued with all pixels in the region. The process stops when no connected pixel meets the criterion for inclusion. The growth tolerance indicates the deviation (positive or negative) from the seed pixel's gray level that is allowed within the region. At the end of this process, the outermost layer of pixels of the region will provide the region's external boundary.

After the boundary of the region of interest has been detected, its pixel locations and values are placed in a circular dynamic array. Using a circular array simplifies traversal of the boundary. The algorithm starts with three boundary pixels: the current, previous, and next pixels. These three pixels are used to determine the normal to the boundary at the current pixel. We take only three pixels at a time in order to simplify the calculation of the normal direction. The algorithm then selects a set of nine pixels that approximates the normal at each pixel on the boundary, by comparing the relative positions of the three boundary pixels selected. The algorithm uses all possible triplet combinations of connected pixels to decide on the approximation to the normal.

Using three connected pixels will produce 20 distinct combinations for bidirectional traversal. The 20 possible tripixel combinations can be divided into eight groups, as illustrated in Fig. 1. Each group represents one of the eight possible normal directions (approximated and limited by the choice of tripixel combinations). Figure 1 also illustrates the discrete approximations to the normals in the eight possibilities considered. In this work we use four pixels inside the region and four pixels outside the region to define the normal. The following equation is then used to calculate the gradient or derivative across the edge pixel:

$$\overline{m}(j)=\frac{1}{4}\sum_{i=1}^{4}\frac{f(i)-b(i)}{2i}\ , \tag{1}$$

where $\overline{m}(j)$ is the mean derivative at the j'th boundary pixel, and $f(i)$, $b(i)$, $i=1,2,3,4$, are the foreground and background pixels along the normal as illustrated in Fig. 2. Note that the edge pixel is not used in this computation. The division by $2i$ is included to take into account the varying distances between the pairs of pixels entering the derivative operation. Note that the differences are computed using pairs of pixels, each having one pixel inside the region and the other pixel outside the region, straddling the edge pixel; the edge pixel itself is not used in computing the differences. This procedure is repeated for all edge pixels (i.e., all pixels on the boundary of the object; see Fig. 3). After all the derivatives have been

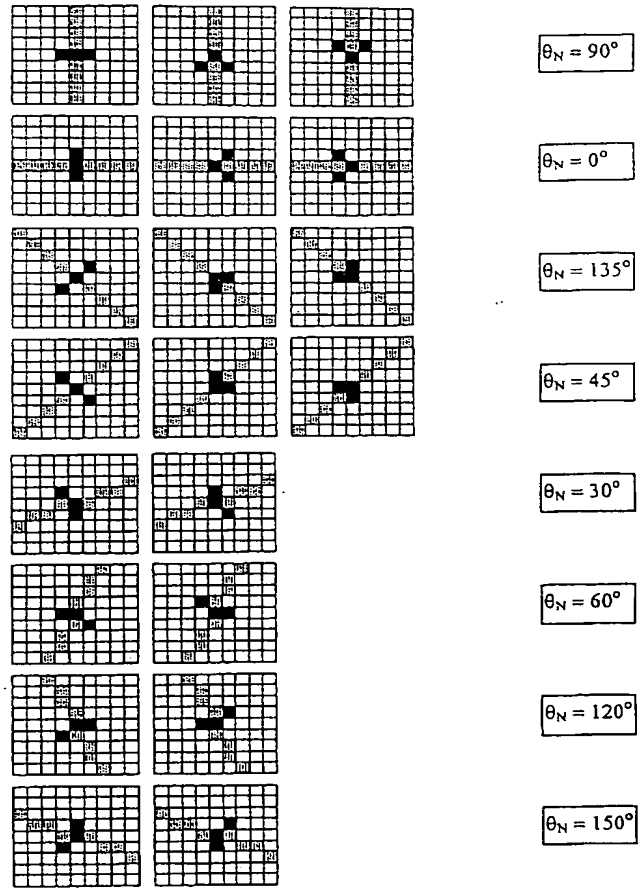

Fig. 1 The 20 tripixel edge pixel combinations (solid pixels) and their approximated normals (shaded pixels), divided into eight groups by the angle of the normal.

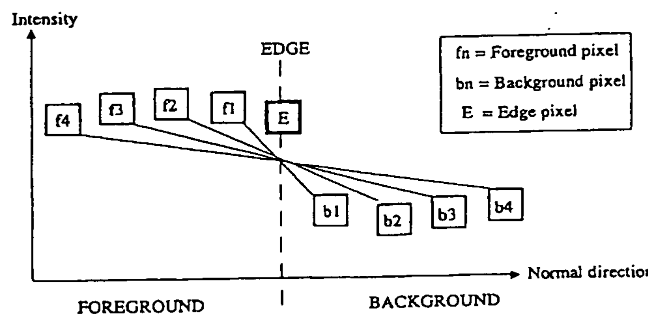

Fig. 2 Pixels used in computing the mean-squared derivative across an edge.

calculated, the rms gradient is computed over all pixels on the boundary. This value is then normalized by the maximum possible rms derivative. The final expression of IEP acutance is then given by

$$\overline{A}=\frac{1}{d_{\max}}\left[\frac{1}{N}\sum_{j=1}^{N}\overline{m}^2(j)\right]^{1/2}\ , \tag{2}$$

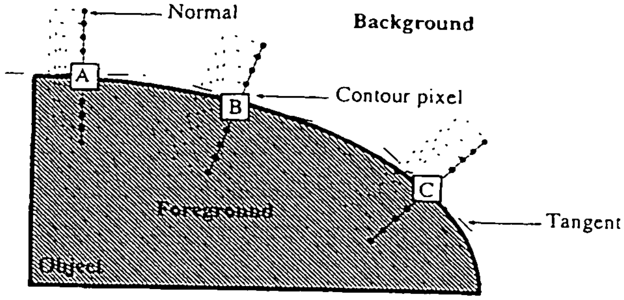

Fig. 3 Calculation of averaged derivatives along normals to the boundary of a region.

where $\bar{A}$ is the IEP acutance, $\overline{m}(j)$ refers to the mean derivative at the j'th boundary pixel as in Eq. (1), N is the number of pixels on the boundary, and d_{max} is the maximum possible rms derivative. For eight-bit digitization, and using the definition of rms derivative as in Eqs. (1) and (2), $d_{max}=132.8125$ (for a uniform object with pixel value of 255 against a uniform background of zero). Using this value of d_{max} limits the maximum value of $\bar{A}$ to unity. Note that $\bar{A}$ is a dimensionless quantity. [Note that Eqs. (1) and (2) in this paper are different from those in our previous paper.[23]]

A summary of the complete algorithm for computation of IEPA is presented as a flowchart in Fig. 4.

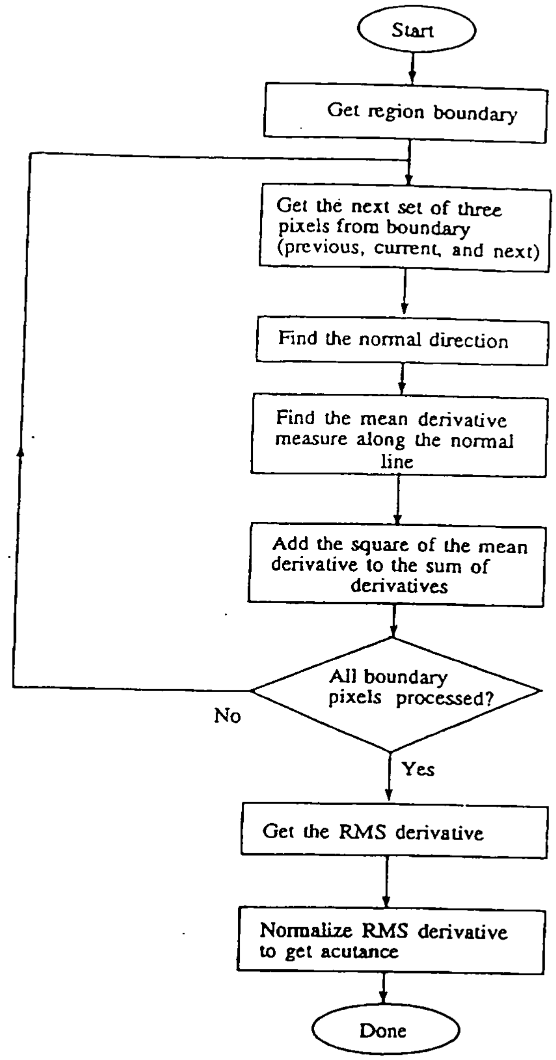

Fig. 4 Flowchart of the algorithm for computation of image edge profile acutance.

4 Evaluation of the IEP Acutance Measure

4.1 *Test Images*

Two images (256×256 pixels, 256 gray levels) were selected to test the acutance algorithm: a digitized image of the letter R [see Fig. 5(a)] and a dragonfly image [see Fig. 6(a)]. The R image was produced by digitizing a 9×11-cm printout of the letter R from a 24-pin dot-matrix printer to a 256×256 array with 256 gray levels; while the image does not have 256 shades of gray, it serves as a simple test image. The R image was selected due to its high contrast and simplicity. Also, the R image contains many different edge patterns, including straight, curved, and sharp corners. The dragonfly image was selected to include intensity variations.

Uniformly distributed random noise with a range of $+50$ to -50 was added to both original images to test the algorithm's performance in the presence of noise; the resulting pixel values were rescaled to the range 0 to 255. The noisy images are shown in Figs. 5(b) and 6(b).

The two original images were blurred using two different methods. The R image was repeatedly blurred using a 3×3 mean lowpass-filter. The dragonfly image was blurred by adjusting the focus of the digitizing camera. Figures 5(c), 5(d), 6(c), and 6(d) show two of the blurred images for each case.

The original dragonfly image in Fig. 6(a) was enhanced using the 3×3 subtracting Laplacian operator[15] to verify if acutance increases with enhancement. Both the processed and unprocessed versions were histogram equalized to permit direct comparison. Finally, the original R image was converted into a binary image to test the maximum achievable acutance value.

The region growing procedure was used to obtain the object boundary for each of the original test images. The edge detection program was found to be quite sensitive to noise. Therefore, and for the sake of consistency, the original image boundary information was used for the noisy, blurred, and processed images. The boundaries detected by the edge detection program are shown overlapping the original test images [see Figs. 5(a) and 6(a)]. The acutance values obtained for all the test images are listed in Tables 1 and 2.

4.2 *Blurring and Sharpening Test*

The first point to note from the results in Tables 1 and 2 is that acutance decreases with blurring. The R image was repeatedly blurred four times using a 3×3 mean lowpass filter while the dragonfly image was blurred by adjusting the camera lens to produce more extensive blurring. In both cases acutance decreases with increased blurring as expected. The enhanced dragonfly images have increased acutance values, with the version after subtracting Laplacian and histogram

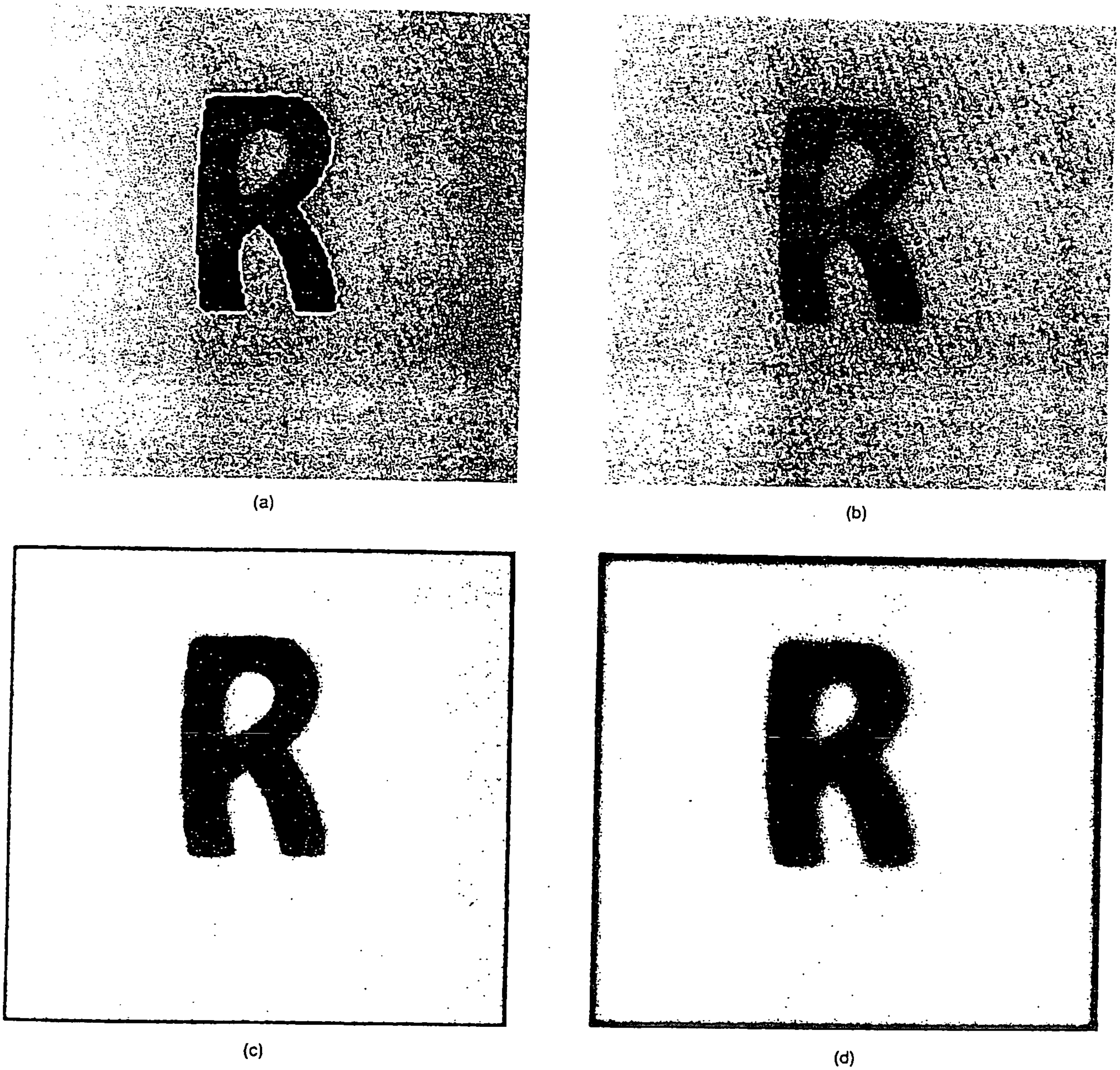

Fig. 5 (a) Original R image with the boundary superimposed; (b) R image after addition of noise; (c) R image after blurring by one pass of the 3×3 mean filter; and (d) R image after blurring by four passes of the 3×3 mean filter.

equalization operations having larger acutance values than the original and the one after histogram equalization alone.

4.3 *Noise Test*

The second test consisted of adding noise to the original images to find out if the algorithm is sensitive to noise or not. From Tables 1 and 2, it is seen that noise does not significantly affect the value of acutance. This is expected, since the algorithm relies on averaged derivative values.

4.4 *Binarization Test*

The final test consisted of converting the original R image into a binary image. A threshold of 128 was used. From Table 1, we see that the ideal (maximum) acutance of 1.0 has been achieved by the binarized image.

5 Conclusion

We have proposed a new, objective, region-based measure of image edge profile (IEP) acutance, based on averaged (rms)

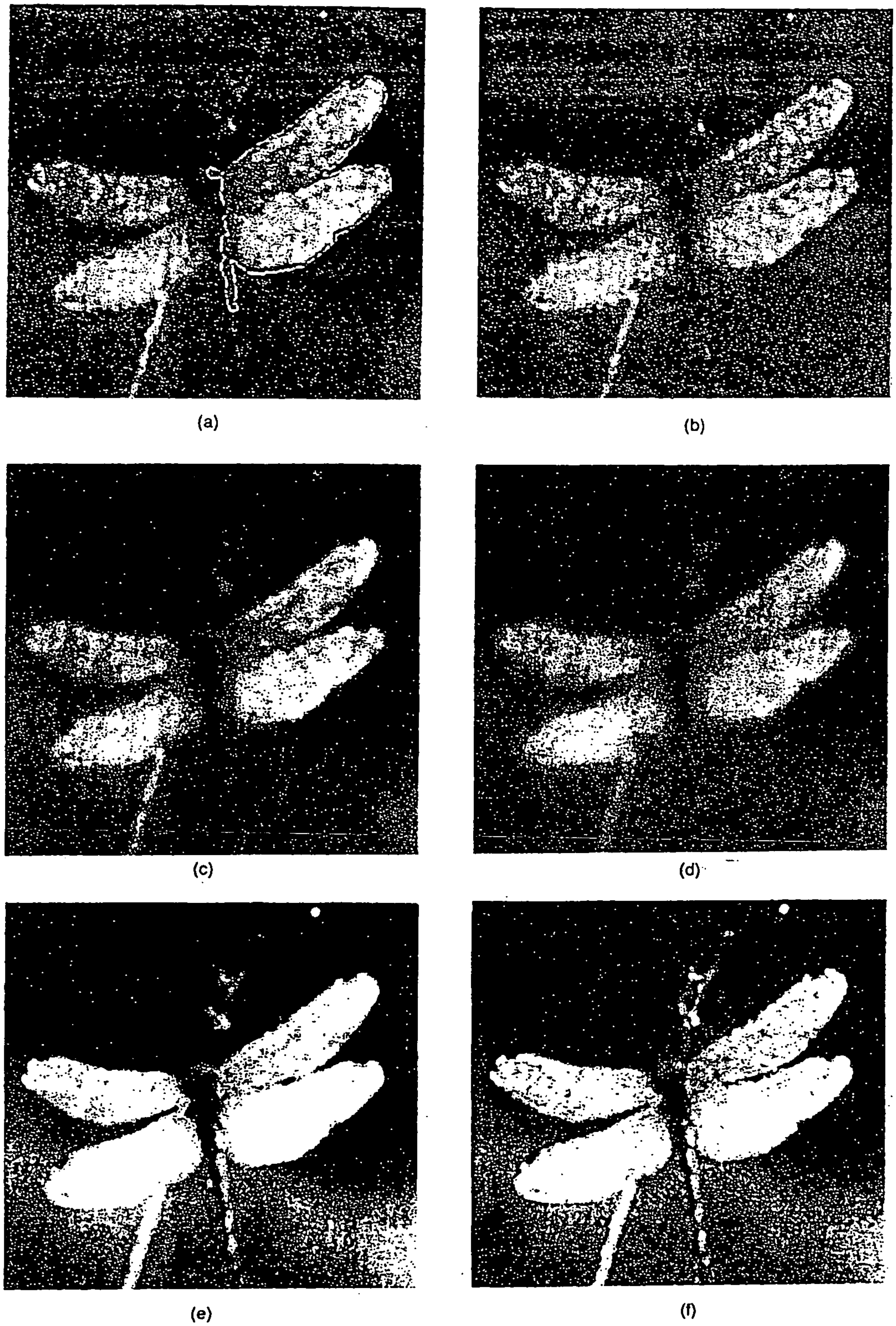

Fig. 6 (a) Original dragonfly image with the boundary superimposed for the region analyzed; (b) dragonfly image with noise added; (c) dragonfly image with level 1 blurring by lens misfocus; (d) dragonfly image with level 2 blurring by lens misfocus; (e) original dragonfly image after histogram equalization; and (f) original dragonfly image after subtracting Laplacian and histogram equalization operations.

Table 1 Image edge profile acutance values of the original, noisy, and blurred versions of the R image.

Image	IEP Acutance
Original R	0.410
Original + noise	0.395
Blurred once	0.373
Blurred twice	0.339
Blurred thrice	0.313
Blurred four times	0.278
Binarized	1.000

Table 2 Image edge profile acutance values of the original, noisy, blurred, and enhanced versions of the dragonfly image.

Image	IEP Acutance
Original Dragonfly	0.331
Original + noise	0.311
Blur level one	0.271
Blur level two	0.213
Original histogram equalized	0.415
Original after subtracting Laplacian and histogram equalization	0.485
Blur level one histogram equalized	0.357
Blur level one after subtracting Laplacian and histogram equalization	0.397
Blur level two histogram equalized	0.294
Blur level two after subtracting Laplacian and histogram equalization	0.313

derivatives computed along normals to boundary pixels of a region of interest. We have demonstrated the efficiency of the measure in reflecting changes due to blurring and sharpening, as well as its performance in the presence of noise. The measure decreases with blurring and increases with sharpening as expected, and reaches the designed maximum value of unity with binarized or two-level uniform objects.

The proposed algorithm is an extension of the first definition of IEP acutance presented by Higgins and Jones.[8] A major improvement in our procedure is that the acutance measure may be computed for any region of interest in a digital image; the work of Higgins and Jones was limited to edge profiles along knife-edge images.

The results reported here demonstrate the variation of the proposed measure of acutance with blurring and sharpening operations. Psychovisual tests need to be conducted in order to establish the correlation of the measure with visually perceived sharpness. Sensitivity of the measure to spatial and gray-scale resolution of digitization also needs to be evaluated.

Our procedure relies on the importance placed on luminance gradients, contours, and edges, as indicated by many researchers (see the review presented in the introduction). It is defined for a specific region of interest in a given image so that it takes into account the nature of the image on hand; on the other hand, the various MTF-based measures do not consider the specific image at all. As such, we suggest that the IEP acutance measure as defined in this work is a suitable measure for comparison of the acutance of a specific image feature or object across a suite of images of the same scene (or patient) produced by different imaging modalities, systems, or parameters, or as a result of various digital image processing operations. The procedure could be extended to compute an "acutance histogram" for an entire image by computing the acutance values for all possible (overlapping or not) regions in a given image. This would be along the lines of the "contrast histogram"[32] we have used to evaluate our region-based image processing algorithms.[33–35]

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